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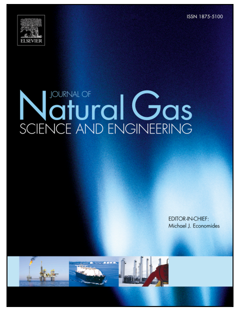

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An Interactive Software Tool for Gas Identification

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Abstract

This paper presents the design of an interactive graphical user interface (GUI) to monitor and quantify a developed electronic nose (EN) platform for gas identification. To this end, an EN system has been implemented using a multi-sensing embedded platform comprised of a data acquisition unit, an RFID module and a signal processing unit. The gas data are collected using two different types of gas sensors, namely, seven commercial Figaro sensors and in-house fabricated 4×4 tin-oxide gas array sensor. The collected gas data are processed for identification by means of dimensionality reduction algorithms and classification techniques where the software implementation and the quantification of these algorithms have been carried out. Subsequently, the GUI was designed to enable several operations. The GUI allows the user to visualize the sensors responses for any selected gas at any point of the acquisition process as well as visualizing the data distribution. Beside, it provides an easy approach to evaluate the EN system performance in terms of data identification and execution time by computing the classification accuracy using a 10-fold cross validation technique. Furthermore, the GUI, which is freely distributed, grants the users the privilege to upload other types of data to enable different pattern recognition applications.

Keywords: Graphical user interface (GUI), Electronic nose (EN), Gas identification, Gas sensor, Pattern recognition

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1. Introduction

Graphical user interfaces (GUIs) are the key elements in the human-machine interaction, as they link the system with its end-users to improve the communication and to simplify both data and information exchange. Moreover, users seek more adaptive interface applications which meet their specific needs in terms of flexibility and easy use of the interface. Hence, GUIs development has become more and more important issue. The main goal of the GUIs is to establish a direct communication between the users and the electronic devices using interactive items instead of text commands. In the GUIs, the different actions are performed through direct manipulation of graphical icons and the visual indicators to present the desired information. A major advantage of GUIs is that they make any implemented system such as electronic nose (EN) systems easy to use, to understand and to evaluate.

The term EN refers to the array of sensors that generate distinct responses to different gases. The EN operates based on the fact that the changes in the gaseous atmosphere alter the sensor properties in a characteristic way [1]. An EN system typically consists of a data acquisition unit equipped with multi-sensor array and an information-processing unit with pattern-recognition algorithms. The multi-sensor array is composed of different types of sensors to react to a wide range of gases in order to generate multidimensional patterns. Each sensor provides a unique response to each gas, and all the individual gas responses are integrated and combined to provide a distinct digital response pattern for each gas. The identification and the classification of the different gases is performed at the information-processing unit using different pattern recognition approaches.

Nowadays, EN systems hold great promises for many emerging fields, where they have been applied efficiently in diseases diagnostic [2, 3], environmental monitoring, food manufacturing [4, 5], biomedical and gas industry applications. For the latter, several studies have proposed solutions to tackle the gas identification problem by using the gas sensors response for each gas as a specific fingerprints in order to discriminate between various gases in the air [6, 7, 8, 9]. Nevertheless, EN system performance is prone to several issues, for instance, the gas sensor properties often change with time, which is known as the drift problem [10], this problem can occur if the gas sensors are exposed to reactive gases for a long period. Another problem that can degrade the EN performance is the non-selectivity problem which relates with the reactivity of a chemical sensor to so called interference gases which are different from the nominal gas towards which the sensor is targeted [11]. Non selectivity can be tackled by exploring a multi-sensing platform, where each sensor response exhibits a different behavior to each gas. Authors in [12] proposed a 4×4 array gas sensor in order to generate different gas responses for the same gas at the same time which will enable a time-efficient scheme for gas samples collection.

However, with the big collected data, the system complexity would increase and the performance of the classifiers could degrade [12]. Therefore, the salient features of data are extracted using dimensionality reduction techniques, such as multidimensional scaling [13], independent component analysis [14], principal component analysis (PCA) and linear discriminant analysis (LDA) [15]. A software/hardware implementation of PCA and LDA for EN system has been carried out in [15], the authors provided a well detailed performance evaluation using data samples collected from seven commercial Figaro sensors [16] and the in-house fabricated tin-oxide 4×4 gas sensor [12].

Gas identification usually explores classifiers taken from pattern recognition applications [17]. For instance, binary decision tree (BDT), K-nearest neighbours (KNN), extended nearest neighbours (ENN) and committee machine (CM) which combines more than one classifier in order to improve the classification. In [18], five classification algorithms have been exploited and combined to implement a gas identification ensemble machine (GIEM) in order to increase the performance of the system.

The contribution of the paper is two folded. First, a performance evaluation study for a proposed EN system has been carried out in details for each of part of its major components. The data acquisition phase has been enabled using two types of sensor arrays, namely, the 4×4 tin oxide-based in-house fabricated sensor array and seven Figaro sensors. A total of 13 distinct gases have been utilized, where for each gas, the samples have been collected for different concentrations in order to build up a large gas database. Afterwards, for gas identification purposes, the salient information from the sensors responses have been selected by extracting the steady state (SS) values. In addition, dimensionality reduction algorithms (LDA and PCA) are applied on the SS values to reduce the computing complexity for the classification process. For the latter, BDT, KNN and ENN have been explored to identify the different types of gases. Furthermore, a CM classifier is presented in which the individual outputs of the previously mentioned classifiers are combined using two different combination rules in order to achieve a superior performance in term of classification accuracy.

Moreover, the presented EN system is accommodated with a user friendly GUI that allows the user to evaluate and monitor the performance of the EN system. The GUI supports the visualization of the different sensors responses to any gas from the acquired group. In addition, the GUI permits to evaluate the performance of the identification process using different parameters for the classifiers as well as different combinations of classifiers and dimensionality reduction techniques. Furthermore, the GUI displays the sample distribution after performing dimensionality reduction to better understand how the data is separated and classified. Finally, the GUI is designed as software tool that can be explored for type of applications based on pattern recognition algorithms.

This paper is organized as follows. Section 2 presents a brief overview about EN systems and discuss the recent related works to design EN platforms for gas identification. Section 3 provides a detailed description of the experimental setup and data collection procedures as well as an overview of feature extraction, dimensionality reduction techniques and the different classification approaches. In section 4, a description of the design of the developed GUI with the functionality of each component is provided. Section 5 presents a detailed evaluation of the proposed EN for the different investigated algorithms as well as illustrative examples regarding the GUI functionalities. Section 6 concludes the paper.

2. EN systems

An EN system represents a tool that provides the detection and the discrimination between different complex odors by deploying an array of sensors in a closed area. The first EN model have been proposed in 1982 [19], the proposed EN have used a metal oxide semiconductor-based sensor in order to identify 20 different odors. Thereafter, a huge interest have been dedicated to the design and the improvement of EN platforms in order to identify a wide range of industrial odors. Various EN prototypes have been proposed in the literature using different sensor technologies, such as metal-oxide [20, 21], conductive electroactive polymers [22], optical [23] and electrochemical gas sensors [24].

A basic EN system is comprised by both hardware and software units:

- An acquisition system: consists of an odor delivery system that transfers the volatile aromatic molecules from the source to the sensor array, a chamber with fixed temperature and humidity to host the sensors and an electronic transistor that converts the chemical signal to an electrical signal.
- A computing platform: consists of a signal processing unit to read, display and perform statistical analysis for the acquired data samples as well as a pattern recognition unit that provides the identification and the discrimination between the different odors.

The sensor array usually consists of non-specific sensors that are treated with a variety of odor-sensitive biological or chemical materials. Each sensor from the array generates a specific smell print for each given known odor, the generated smell prints are used to build up a database to train the pattern recognition system so that unknown odors can subsequently be classified and identified.

The utilities of EN has spread widely in a variety of fields and applications. For instance, food industry presents a good example where EN systems have been applied to enable several tasks, such as food quality control and authentic product assessment [25, 26, 27], dairy product freshness [28, 29], and aroma classification in food products [30]. EN systems have been applied as well for agriculture applications to identify insect infestations and to monitor plant physiological processes [31, 32]. In addition, some of the other common utilization of EN includes indoor air monitoring [33], diseases diagnosis [34, 35], ambient assisted living [36], etc.

Moreover, gas industry has explored widely the concept of EN for gas identification. One of the most witnessed applications is environmental-pollution monitoring, where EN platforms have been employed efficiently for real time air quality monitoring and pollution-emission events detection via sensor monitoring network [37] as well as pollution sources localization [38]. In addition, EN systems can be deployed in indoor areas to detect fires at chemical storage units, to maintain chemical security at harbor entrances or importation ports [39], to detect any gas leakage and hazardous elements in the gas plants pipelines [40, 41, 42], as well as to provide a prompt warnings in case of accumulation of toxic and explosive gases fumes in enclosed areas.

Two different approaches have been considered in the design of EN platforms, hardware based and software based approaches. Various EN hardware-based implementations have been presented in the literature. Authors in [43] evaluated an EN platform based on both linear DT and non-linear DT classifier. The classification is performed with and without dimensionality reduction, where the obtained classification accuracy was 99.55% and 94.55% for linear and non-linear DT, respectively. Moreover, The authors validate their simulation results by implementing the linear DT without dimensionality reduction on a field programmable gate arrays (FPGA). Furthermore, an FPGA implementation of a CM for gas identification is proposed in [44] by exploring five different classifiers to improve the identification rate. The CM combines a weighted output from multilayer perceptron (MLP), Gaussian mixture model (GMM), radial basis function (RBF), KNN and probabilistic PCA. In addition, the authors have applied PCA to reduce the dimensionality of the features prior to the classification.

The obtained results reveals that CM has achieved a classification accuracy up to 95% which is much higher than the individual classification accuracy obtained by each classifier which ranges between 79.1% and 92.3%. Moreover, another FPGA-based implementation of EN platform using MLP classifier is presented in [45], the gas samples were collected using an array of eight micro-hotplate-based SnO_2 thin film gas sensors to overcome the non-selectivity problem. The EN system uses MLP as a classifier with eight input and five output neurons corresponding to the eight sensors and five type of gases respectively, the best obtained accuracy is 93.75.

On the other hand, software based EN have been carried out as well. A software implementation of an EN is presented in [46] using a gas array consisting of 16 sensors. The main contribution of this work is to use temperature modulation (TM) in the collection of the gas samples, this approach generates multiple responses corresponding to multiple temperatures. The collected samples are combined using self organized maps (SOM) to create a 2D image that will be the signature of the gas. After generating an image for each gas at a given concentration, image moments (IM) are extracted and LDA algorithm is applied to reduce dimensionality of the features prior to the classification. In the latter, five classifiers have been quantified KNN, GMM, MLP, RBF and PPCA, where GMM has achieved the highest accuracy of 96.2%. In [47], an odor monitoring system is presented based on eight SnO_2 sensor array, this work combines genetic algorithm (GA) and artificial neural network (ANN) to develop a neural-genetic classification algorithm (NGCA). It is worth mentioning that all sensors outputs values are normalised between 0 and 1 then smoothed moving average (SMMA) is used prior to the classification stage to remove any noise in the signals. Results have shown that the system reaches a classification accuracy of 95% outperforming the performance obtained using ANN (82%) and GA (91%). Moreover, a comparison study has been performed in [48] to compare the performance of density models against discriminant functions as classifiers for gas identification. The classifiers based on density models are KNN, GMM and generative topographic mapping (GTM) while the ones based on discriminant functions are RBF, MLP and generalized linear model (GLM). Additionally, PCA, LDA and neuro-scale (NS) techniques are also evaluated as preprocessing techniques. The results show that the best performance is obtained when PCA is used for preprocessing and GMM for classification reaching an accuracy of 92.7%. Authors in [49] presented an improved technique for EN based on the rank order (RO) by using probabilistic rank score coding (PRSC). The RO methods uses spikes that represent a unique signature for each gas. However, due to the low repeatability of the sensors responses when targeted with the same gas and the same concentration, the temporal spiking sequences may vary which will decrease the performances of the system. To overcome this issue, PRSC is used and the probability of every spiking sensor is tabulated at every rank. This tabular information is used for classification. The EN is tested using two different sets of sensors and in both cases, a 100% accuracy is reached. A similar work that uses PRT is presented in [50]. Furthermore, authors in [51] presented two improved version of KNN for gas identification. The first one is cluster-k-nearest neighbors (CKNN) and the second one is tree-CKNN. Both techniques show an improvement compared to KNN without using dimensionality reduction with an accuracy of 98.7% for CKNN and 100% for tree-CKNN.

3. Proposed System Overview

The EN system shown in Fig. 1 consists of two main units, a data acquisition unit where the data from various gases are collected and a processing unit where the most useful features of the collected data are extracted, processed and used for gas identification.

For the acquisition process, two types of SnO2 based sensor array are used, the first sensor array consists of seven commercial Figaro sensors [16] while the second one is the 4×4 in-house fabricated sensor array [12]. After data acquisition, features extraction techniques are explored along with different dimensionality reduction techniques to assemble a training set, a validation set and a testing set. The final stage of the EN system is gas data classification where several classification approaches are adopted.

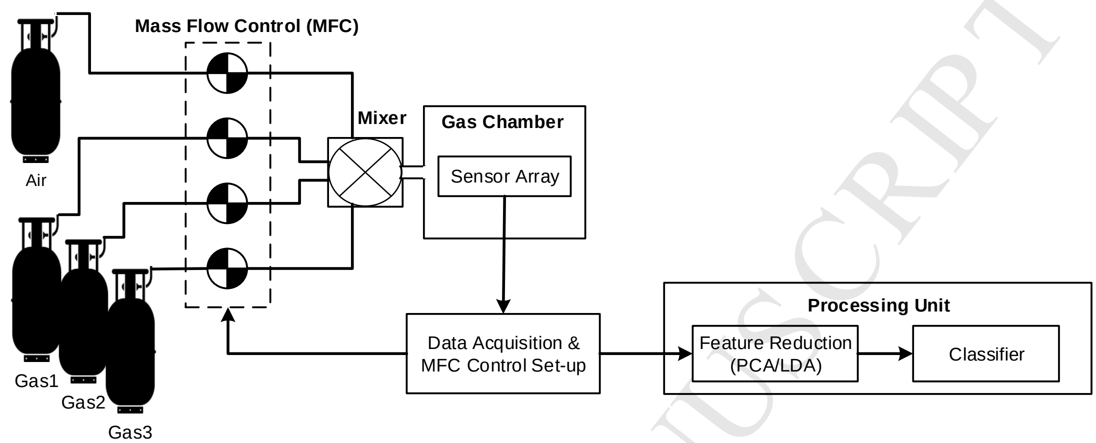


Figure 1: EN System for Gas identification [15]

3.1. Data Collection

The experimental setup to collect the data consists of a sensor array located inside a gas chamber. The latter has two orifices, one to serve as an input for the in-flow of gases and the other one as an exhaust to evacuate the gases. Multiple gases are stored in various cylinders connected to the gas chamber individually through several mass flow controllers (MFCs). A control unit is connected to the MFCs to control the gas flow to the sensor array via a data acquisition (DAQ) system in order to collect and sample the sensors responses. In total, four data sets are collected, two using the 4×4 in-house sensor array and two using seven Figaro sensors. Each of these data sets is stored as an $M \times N$ matrix, such that N represents the number of the used sensors and M denotes the number of samples collected from each sensor.

3.1.1. The 4×4 Sensor Array

Two different data sets have been collected using 4×4 array gas sensor. In the first one, samples were collected from three different gases, carbon-monoxide (CO), hydrogen (H_2) and ethanol (C_2H_6O). For each gas, 10 different concentrations were used (20, 40, 60, 80, 100, 120, 140, 160, 180 and 200 *ppm* in air).

The procedure to collect each gas takes 1000 s (second) for each concentration value. First, the air is injected through the sensors for a period of 750 s followed by 250 s of exposure to the new concentration of gas. The overall time for 10 concentrations becomes $10,000$ s. Each concentration cycle is performed twice, hence, 60 patterns are collected in total.

In the second data set, five different gases are examined, namely, Benzene (C_6H_6), carbon monoxide (CO), formaldehyde (CH_2O), nitrogen dioxide (NO_2) and sulfur dioxide (SO_2). Three different operating temperatures (OTs) (200° C , 300° C and 400° C) for each gas were used to investigate the effect of OT on the sensor response behavior. An analytic study to determine the optimal temperature for gas sensor is presented in [52]. A concentration range of 0 to 5 ppm is used for C_6H_6 and CH_2O. Whereas for CO, NO_2 and SO_2, the concentrations range from 0 to 250 *ppm*, 0 to 10 *ppm* and 0 to 15 *ppm*, respectively. For each gas, the data extraction is carried out for four concentration values from its concentration range. Thus, the selected concentrations for C_6H_6 and CH_2O are 0.25, 0.5, 2.5 and 5 *ppm*, while for CO the concentrations are 5, 25, 150 and 200 *ppm*. Similarly, for NO_2 they are 1, 3, 5, 10 ppm and for SO_2, the concentrations 1, 2, 5 and 25 *ppm* are selected. The process of data acquisition for each gas is repeated three times for each concentration such that each gas sensor has 12 patterns/temperature and a total of 36 patterns for three temperatures.

3.1.2. Figaro sensors

Similar to the approach used in the 4×4 sensor array, two different data sets were collected using the seven Figaro sensors. In the first set, data from four different gases have been collected, the gases are carbon-di-oxide (CO_2), hydrogen (H_2), ammonia (NH_3) and propane (C_3H_8) using the following concentration rates (20, 40, 60, 80, 100, 120, 140, 160, 180 and 200*ppm* in air). To collect the data, the sensors are exposed to air for 750 s, then, the they are exposed to the gas for 500 s, resulting in a period of 1250 s to collect gas samples for each concentration.

For the second data set, five gases have been selected (C_6H_6, CO, CH_2O, NO_2 and SO_2). The data of each gas has been collected for five different concentrations. The details for the concentration ranges used for each gas are listed in Table 1.

Table 1: Concentration Ranges for Different Gases

Gas	**Concentration Range (ppm)**
C_6H_6	0.25-5
CH_2O	0.25-5
CO	5-200
NO_2	1-10
SO_2	1-25

Fig. 2 and Fig. 3 display the sensors responses to the CO gas collected by 4×4 array sensor and CO_2 gas collected form the seven Figaro sensors, respectively.

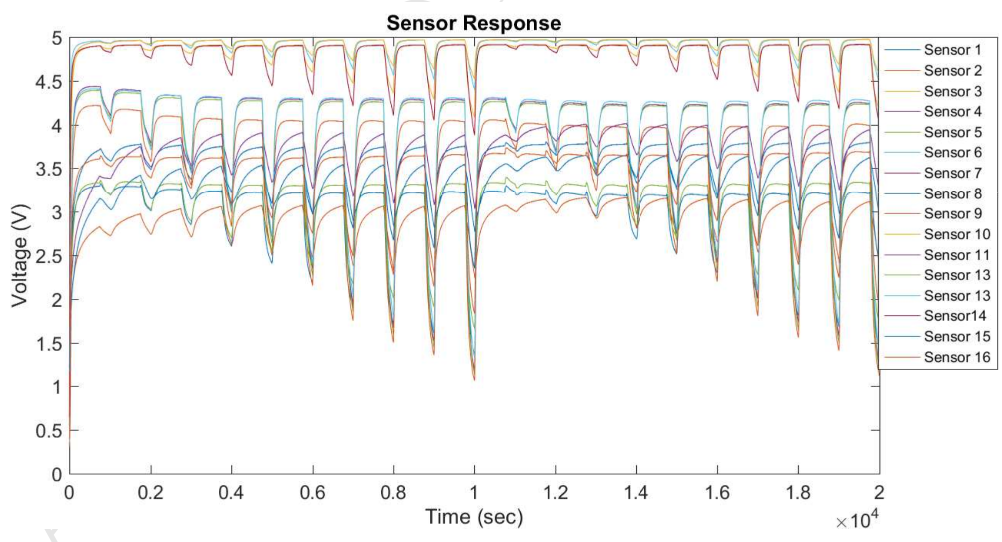


Figure 2: Sample of sensors responses for carbon monoxide (CO) by 4×4 array sensor

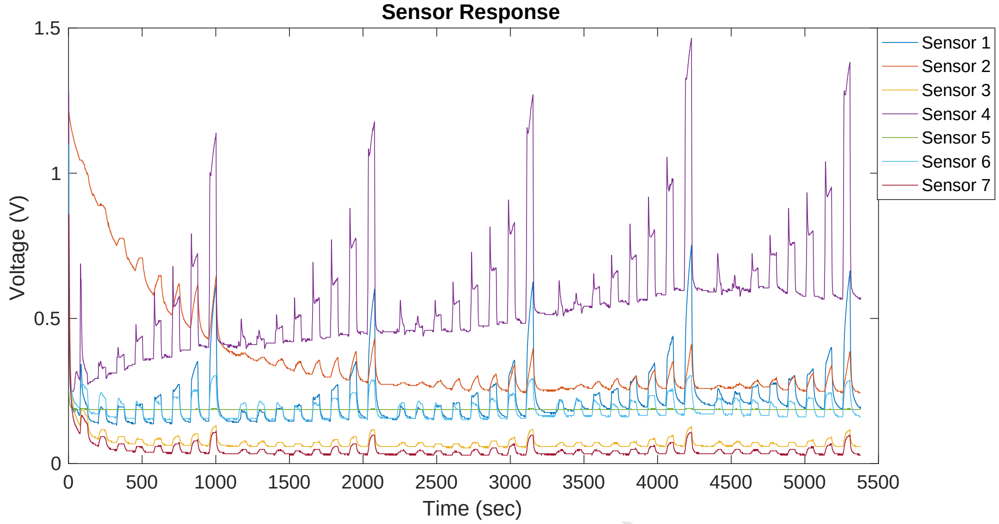


Figure 3: Sample of sensor responses for carbon-di-oxide (CO_2) by seven Figaro sensor

3.2. Features Extraction

After data collection, the most significant features of the data have to be extracted by means of feature selection techniques. Feature selection aims to identify the features that provides significant information about the data and discard the features that are irrelevant and do not contain any discriminatory information. The quality selected features have a crucial impact on the classification performance, thus, a poor selection will reduce adversely the performance of the system.

For gas identification problems, various techniques to generate descriptive parameters from the responses of the sensors can be adopted [53]. However, the most common used features are the steady states (SS) values. SS values corresponding to all gases and concentrations are extracted manually form the data by taking the values corresponding to the end of each gas injection period. The extracted features are divided into training set and testing set. In addition, a class label set is assigned to the data where each sample is assigned with a specific label.

3.3. Dimensionality reduction

The extracted features (SSs values) can be used for training and testing directly or dimensionality reduction techniques such as PCA and LDA can be applied to these extracted features.

3.3.1. Principle component Analysis

PCA is used to transform the sample data from m-dimensional space to n-dimensional space such that $m > n$ [54]. Each component in n-dimensional space is known as principal component (PC) which contains most of the information about data from lower PC to upper PC which means that the first principal component (PC1) capture the most useful information about the data.

3.3.2. Linear Discrimination Analysis

In machine leaning and pattern recognition applications, LDA is widely used for dimensionality reduction at the pre-processing stage [11]. LDA projects the data onto a lower-dimensional space while maintaining a good class-separability in order to avoid the overfitting problem. The aim of LDA is to find the component axes known as discriminant functions (DFs) that maximize the variance between inter classes of the data as well as reduce the inner classes variances in the same time.

3.4. Data Classification

After the feature extraction and the dimensionality reduction phases, data classification is performed. The training data and the label class matrix are used as an input for several identification algorithms in order to classify the gas data.

3.4.1. Binary Decision Tree

BDT is a supervised learning technique with a set of labeled data as the input of the learning algorithm and a binary tree as its output [15]. The generated tree is used for the classification of a the testing data. BDT training algorithm requires two inputs, the training data set and the class label set.

3.4.2. K-Nearest Neighbour (KNN)

KNN algorithm is a classification technique that has been well considered in pattern recognition applications. KNN classifiers are based on learning from the neighbours of the corresponding test sample by comparing a given test (distance function) with training samples that are similar to it [55]. The performance of KNN is governed by the parameter K which represents the number of neighbours that have to be considered for the test. The classification of any test sample is obtained by using a majority vote among the nearest selected K elements, and the sample is assigned with the same class as the most common neighbours.

3.4.3. Extended Nearest Neighbour(ENN)

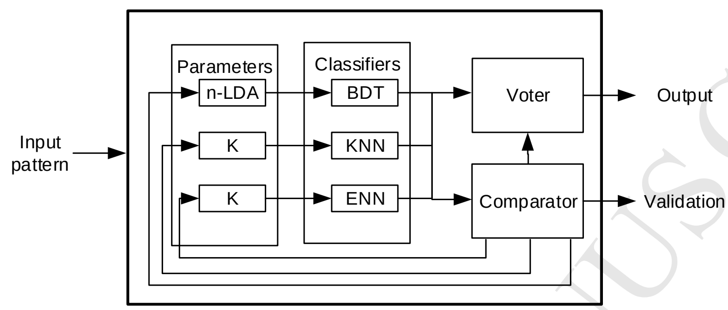
ENN classifier is an enhanced version of KNN. The main idea of ENN is to make a prediction for any given test sample based on a 'two-way communication' style [56]. ENN uses the entire training set in the classification instead of just K-neighbours of the test sample data in order to find samples that consider the test sample as one of their K-nearest neighbours.

3.4.4. Committee Machine

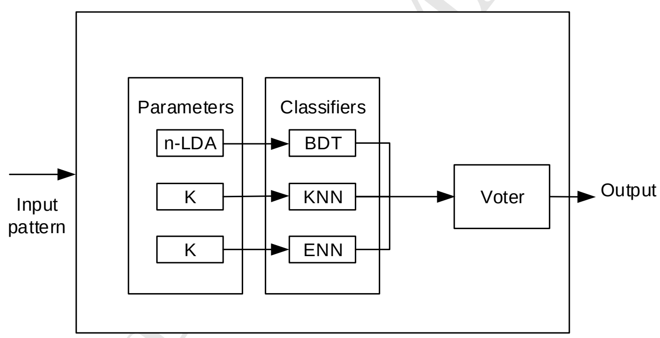
CM is a classification approach that combines different classifiers in order to improve the performance of data identification. In the proposed EN system, two different approaches for designing the CM were adopted, with and without feedback validation.

CM With Feedback Validation Approach. The proposed CM with feedback validation shown in Fig. 4(a) consists of two main steps, validation and testing. The validation step determines the best parameters for each classifier using feedback operation where the decision of each classifier is compared with the actual class label of the validation sample. If the classification does not match the corresponding class label, the parameter of that classifier will be updated. At the testing stage, only the best parameter of each classifier is used.

The CM Without Feedback. This approach combines three classifiers, each with three parameter values that are pre-selected. After performing the classification of three classifiers each with its respective parameters, the test sample is classified based on a majority vote decision as shown in Fig. 4 (b).



(a)



(b)

Figure 4: Committee Machine (a) With Feedback Validation Approach (b) Without Feedback

4. GUI Design

The main objective of the GUI is to provide the users with an interactive application that meets their needs. Subsequently, in the design of GUI, several principles such as clarity, simplicity, consistency, flexibility and user error tolerance have to be satisfied.

Therefore, an interactive Software tool presented in a GUI has been developed for the proposed EN system using MATLAB 2014a software. The main purpose of the GUI is to represent all the EN system parts. The navigation paradigm for the developed GUI supports three main activities. It allows the user to easily visualize all the sensor responses, to evaluate all the possible combinations of the explored pattern recognition techniques used for gas identification and to analyze the of the extracted features. Furthermore, the GUI provides the user with the ability to input his own data to be classified for various applications that are based on pattern recognition and machine learning.

Moreover, the developed GUI can be used to emulate the response of the sensors to the different gases. The GUI can be connected offline to a Zynq SoC platform that have been used to implement DBT and KNN for gas identification in [15, 57].

The developed GUI presented in Fig. 5 consists of three main panels, data visualization, data identification and data distribution. In order to fully exploit the GUI, the data has to be first selected and validated from the data visualization by choosing the appropriate sensor and data set or by choosing the user specific data. Thus, each time the user selects a sensor type and a data set, a validation is required by enabling the "Load Data" push-button. For classification, a variety of combinations of the previously mentioned algorithms can be selected using different parameters. The data identification panel provides the user with the ability to perform a detailed evaluation of the EN in terms of classification accuracy and execution time. Also, features distribution after applying LDA and PCA can be analyzed via the data distribution panel. In addition, the GUI is accommodated with alert message pop-ups to guide the user in order to navigate easily through the GUI.

Furthermore, the developed GUI which serves as a standalone executable file application is freely available for users to be explored for applications of pattern recognition. The GUI can be downloaded from the software supplementary martial associated with the paper or alternatively from the link below [1]. It is worth mentioning that the user requires a Matlab 2014a version installed in his/her computer in order to run the GUI application[2].

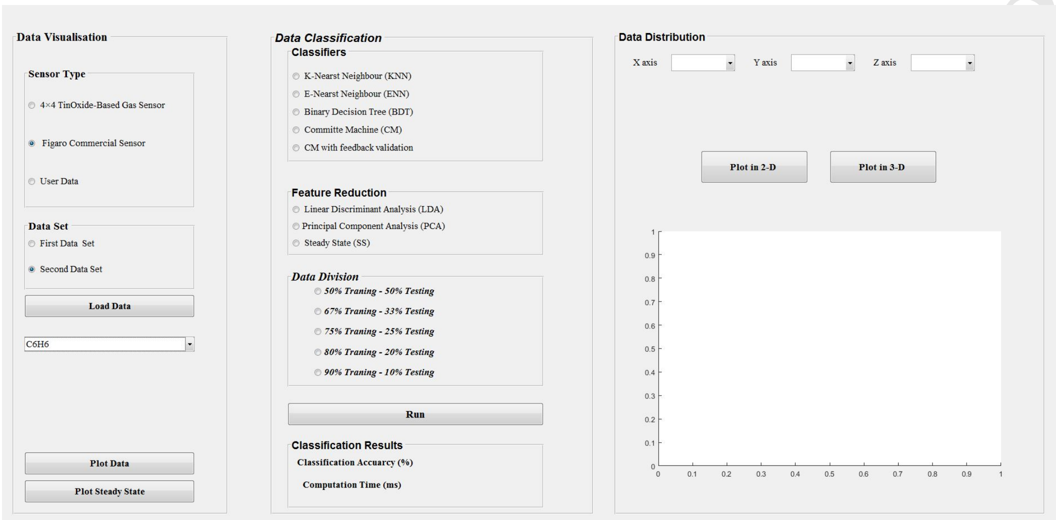


Figure 5: GUI for Gas Identification

4.1. Data visualization

The first panel of the GUI is data visualization which is dedicated mainly to the sensing part of the EN system. This panel allows the user to display clearly the sensors responses to the different selected gases. The design of this panel permit the user to easily select any data from the list of the various collected gases to display . The visualization panel is designed as follow:

- "Sensor type" panel, where the user can select either the gas data collected from Figaro sensors or the gas data collected from the 4×4 in-house fabricated sensor.
- "Data set" panel to select either the first or the second data set.

[1] https://drive.google.com/drive/folders/0Bz-gwsNALUu9ZmRpS3FXT0xuZlk
[2] For more information, contact (hamza.djelouat@qu.du.qa,djelouat.hmz@gmail.com)

- "Gas list": in order to pick up an individual gas to visualize.
- Two push-button to display the sensor response and steady state values for the selected gas.

Beside, by selecting the push-button labeled "User Data", the user will be able to upload his data to the GUI for identification. The data should be in a MAT-files format. Therefore, by selecting "User Data" option, the user can upload two data sets. The first one will be dedicated to the raw data that are collected from different channels or sensors, this option will allow the user to visualize the behavior of the acquired data. The different types of acquired signals should be saved individually in the data raw file in order to be visualize separately.

However, for data identification, since feature extraction techniques differ from application to another, the user should input the matrix that contains only the features to be used for classification. The features matrix should be of dimension $m \times n$, where m denotes the number of samples to be classified, and $n-1$ denotes the number of features and the last column of the feature matrix is reserved for the data class label column vector.

4.2. Data Classification

Classification panel allows the user to evaluate the identification performance of the EN system. Using this panel, the user will have the possibility to evaluate the performance for a wide range of "features reduction approaches- Classification technique" combinations. "Data Classification" consists of four main panels, classifiers, feature reduction techniques, data division and results. In the classifiers panel, one of five classification approaches along with its specific parameter can be selected. Classification techniques include individual classifier (BDT, KNN and ENN) and CM with its two different designing approaches. Features reduction panel allows to use the collected data directly by extracting the SSs values or to apply dimensionality reduction techniques using either LDA or PCA. Computing classification accuracy using the cross validation approach is used in the proposed EN system and it can be performed using the data division panel in the GUI to determine the number of folds for training. After selecting the combination desired, the classification accuracy and computation time is displayed in the results panel.

4.3. Data distribution

In this panel, the distribution of the extracted features after performing features reduction techniques (LDA and PCA) can be displayed either in 2D or 3D.

The utility of samples distribution is that it will provide the user with a better understanding about the obtained classification accuracy, as it will will allow the user to visualize the separation between the samples of each distinct class in both 2D and 3D planes. In addition, by visualizing the samples distribution and computing the classification accuracy, the user can determine the best approach to further improve the identification process in case of bad classification accuracy either by changing the dimensionality reduction approach if the samples distribution seems to be highly overlapping or by adopting a new classifier if the samples are well separated.

5. EN Software Implementation Results

In order to quantify the performance of the proposed EN system, a software implementation of the aforementioned feature extraction and pattern recognition techniques has been carried out using Matlab computing software. The implementation allows to visualize the extracted feature, to analyze the distribution of features after applying dimensionality reduction algorithms and to evaluate the identification in terms of classification accuracy and execution time.

Prior to dividing the data into training and testing sets, Fig. 6 presents the distribution of the extracted features from the first set from seven Figaro sensors after PCA is performed. Only the four best PCs are plotted, a wide separation between the data samples from each gas is observed, especially for PC1, PC2, PC3, this separation is considered as a good condition for data classification.

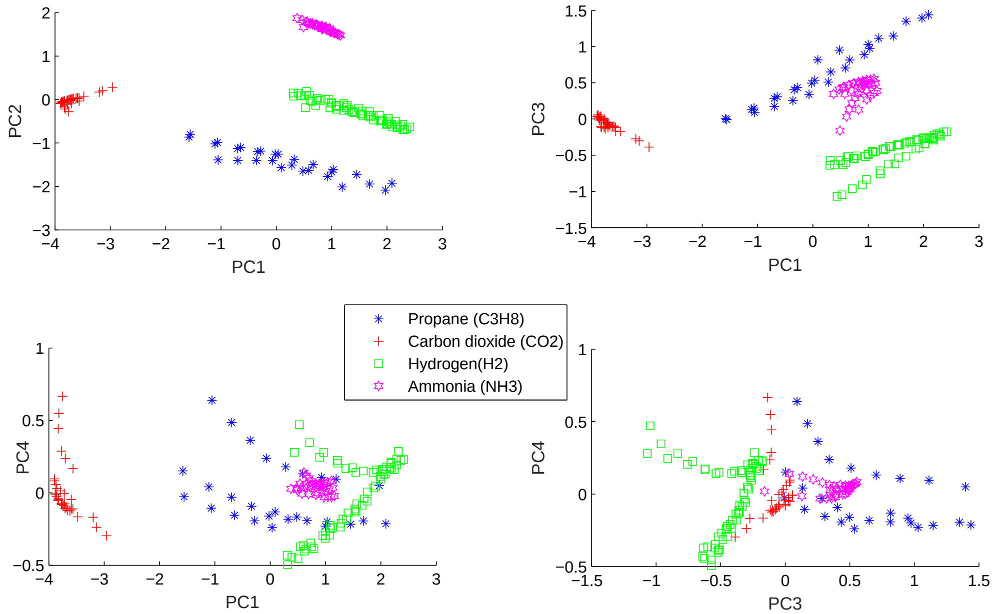


Figure 6: Features Distribution for First Data Set Collected from Figaro Sensors Using The Best 4-PCs

LDA presents a good approach as well, Fig.7 and Fig. 8 illustrate the features distribution after performing the first two discriminant functions (2-DF) for the data collected from seven the Figaro (4 gases) sensors and 4×4 sensor array (3 gases), respectively. The features of each gas tend to be grouped in a unique cluster providing a clear separability between between the distinct gas, this wide separation presents a good scenario for data classification.

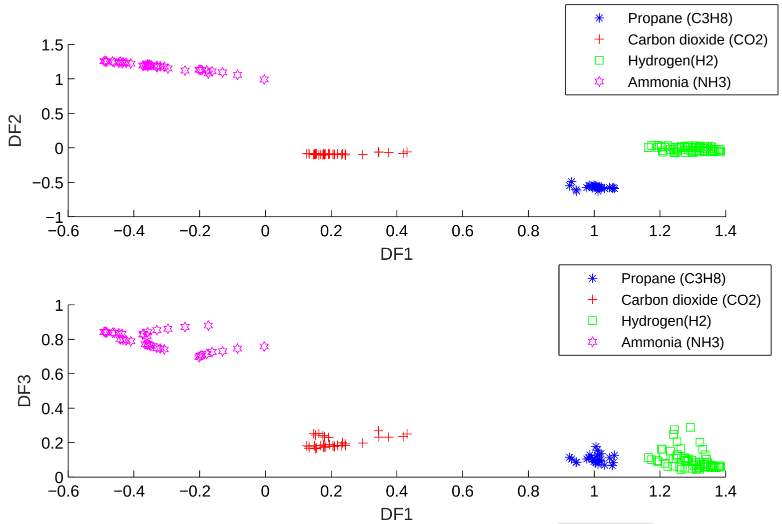


Figure 7: Features Distribution for First Data Set Collected from Figaro Sensors Using DF1 and DF2

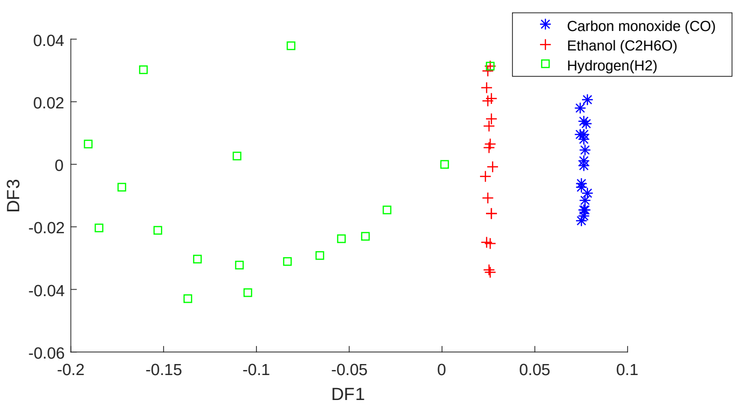


Figure 8: Features Distribution for First Data Set Collected from 4×4 Sensor Array Using DF1 and DF2

Beside dimensionality reduction, gas identification requires incorporating several classification algorithms. However, to fully assess the performance of the system, cross validation is adopted to estimate the general performance and the stability of the learning procedure. Cross validation is performed by splitting the overall data into two main parts. Part of the data is used to train the algorithm whereas the remaining part is used for testing and validation. k-fold cross validation [58], for instance, is one type of cross validation techniques, where the whole data set is split equally, if possible, into k subsets. Next, $k-1$ subsets are used as training data and only a single subset is used for validating and testing. The cross validation process is performed k times, in which, each of the k subsets is used as the testing group only one single time. The classification accuracy is averaged over the obtained k results from the folds. The main advantage of this approach is that all the data included are used for training and testing and each sample is tested once.

Therefore, an intensive number of Matlab implementations for several combinations of dimensionality reduction algorithms (PCA and LDA) and classification approaches (BDT, KNN, ENN and CM) have been carried out to quantify the performance of the EN platform. For each algorithm, different parameters have been used to analyze their influence on the identification performance. In addition, Classification accuracy and execution time are used to quantify the performance of the the proposed EN system.

Classification accuracy is computed as the ratio between the number of the correct predictions over the total number of samples in the testing data set. Additionally, the software implementations is repeated 100 times, where at each trial, the data sets are reordered column-wise. All the reported results presented in this section are obtained by applying a 10-fold cross validation approach.

Table 2 and Table 3 present the classification accuracy obtained by all the classifiers using data collected form 4×4 sensor array and Figaro sensors, respectively. For both KNN and ENN, setting up the parameter $k = 1$, renders the best results, therefore, all the reported results herein for ENN and KNN are obtained with $k = 1$.

The obtained results shows that exploiting CM classifiers improves the classification accuracy over individual classifiers for both sensor types. Moreover, CM with feedback validation outperforms the rest of the classifiers regardless whether dimensionality reduction techniques are used or not with classification accuracy up to 98.89% for the 4×4 sensor array and 100% Figaro sensor.

For the individual classifier, KNN and ENN provide a better classification accuracy than the one obtained by BDT with a maximum classification accuracy of 99.34 % for KNN with data from the Figaro sensors using 5 PCAs.

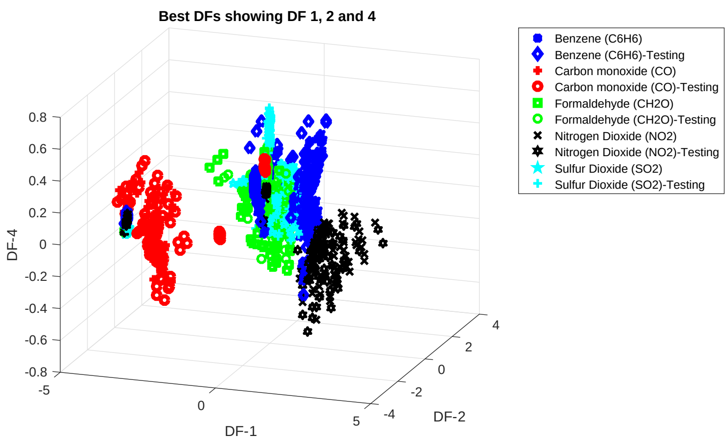
Table 2: Classification Accuracy (%) for Data Collected From 4×4 Sensor array

	Classification features				
	Steady states	4 PCAs	5 PCAs	3 LDAs	4LDAs
BDT	87.5%	87.5%	89.29%	92.44%	91.66%
KNN	94.79%	90%	91.57 %	95.33%	94.27%
ENN	93.22%	88.02%	92.70%	94.27%	93.75%
CM without feedback	95.78%	90.10%	93.75%	98.42%	97.36%
CM with feedback	96.31%	95.55%	98.89%	98.89%	98.89%

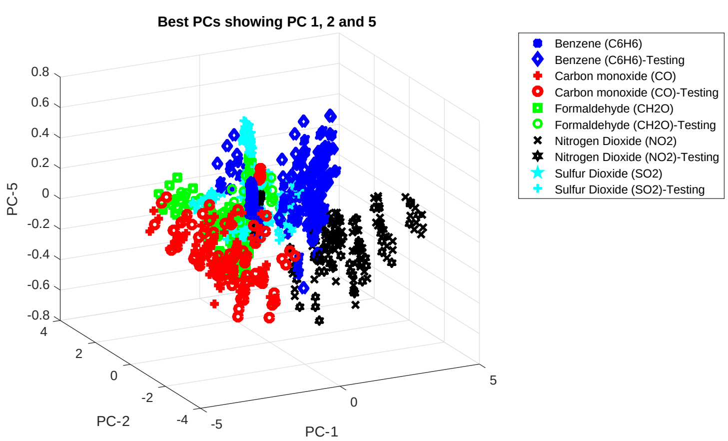
Table 3: Classification Accuracy (%) for Data Collected From Figaro Sensor

	Classification features				
	Steady states	4 PCAs	5 PCAs	3 LDAs	4LDAs
BDT	94.56%	96.52%	95.43%	95.43%	97.60%
KNN	99.18%	98.47%	99.34%	98.04%	98.4%
ENN	99.04%	98.91%	99.34%	98.04%	98.4%
CM without feedback	92.82%	92.82%	92.60%	94.42%	97.36%
CM with feedback	99.04%	100%	99.34%	100%	100%

In terms of the best features to be used for classification, exploring LDA with 3 DFs shows to render the best classification accuracy for all classification approaches using data collected from the 4×4 sensor array with classification accuracy of 95.33 % using KNN classifier. The superiority of using LDA can be explained by the fact that LDA provide a better separation for data compared to PCA. Fig. 9 (a) and Fig. 9 (b) show the distribution of the training samples and testing samples using LDA and PCA, respectively, it can be readily seen that a more clear and wide data separation is obtained with LDA compared to PCA.



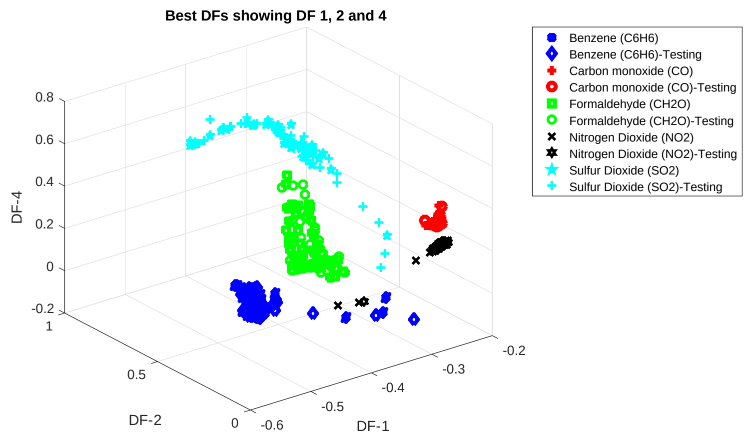
(a)



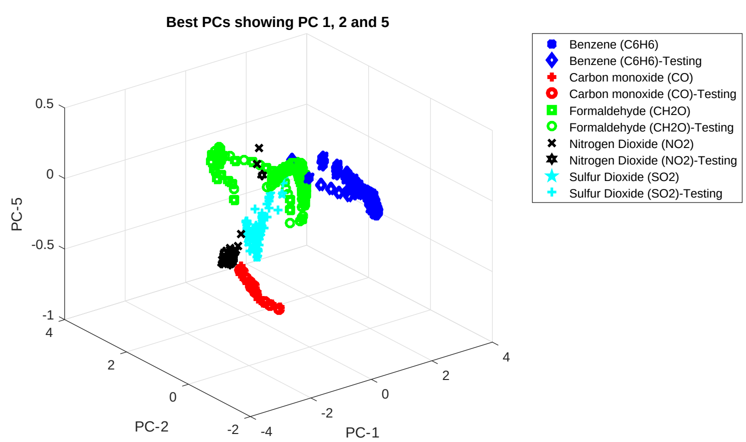
(b)

Figure 9: Comparison between feature Distribution After Performing PCA and LDA for Data Collected from 4×4 array sensor

Whereas, for the data collected from the Figaro sensor, applying PCA renders the best classification accuracy up to 100 % with 5 PCs. Features distribution after performing LDA and PCA are displayed in Fig.10 (a) and Fig.10 (b), respectively. However, no remarkable difference can be observed between the two algorithms and both LDA and PCA show to provide a good class separability.



(a)



(b)

Figure 10: Comparison between feature Distribution After Performing PCA and LDA for Data Collected from Figaro Sensors (a) LDA, (b) PCA

The software implementation execution time for all the classifiers is also examined. The implementation timing is controlled mainly by two parameters, the speed of the processor and the number of tasks handled by the processor. To decrease this dependency, we maintain the same environment for all the algorithms by implementing them in a single program. Since the 10-fold cross validation is used, the reported results are averaged over 10 folds. It is worth mentioning that the operating system where the algorithms have been implemented is 64-bit Windows 7 professional, with a processor of an Intel core I7-3770 @3.4 Ghz CPU and a RAM of 16.0 GB.

The execution time in (ms) for the different classification techniques is presented in Table 4 and Table 5 for 4×4 sensor array and Figaro sensors, respectively. Results clearly show that all individual classifiers outperform both CM approaches in terms of computation time, in fact, this result is expected due to the additional complexity in the CM designing. CM without feedback needs to have the outputs of all the individual classifiers in order to make its decision, therefore, even if parallel computation is performed, the execution time for CM without feedback will be at least the sum of the time of the slowest classifier with the time for majority vote step. In the case of CM with feedback validation, the step for selecting the best parameter will be the most time consuming process and it will increase the execution time. Beside, ENN classifier shows to be the best algorithm that achieve the results in minimum amount of time compared to the other investigated techniques with a 91 ms using SSs values. Therefore, in selecting the appropriate approach for gas identification, a trade-off between the classification accuracy and the execution time has to be made following the application-specific requirements.

Finally, the results show that the execution time for 4×4 array sensor is less than the seven Figaro sensors for each classification approach, this is due to the fact that the data sets collected from Figaro sensors are larger than the ones collected from 4×4 array sensor.

Table 4: Execution Time (ms) For Data Collected From 4×4 Sensor Array

	Classification features				
	Steady states	4 PCAs	5 PCAs	3 LDAs	4LDAs
BDT	177	189	165	129	126
KNN	130	164	175	140	146
ENN	91	114	112	104	102
CM without feedback	350	464	420	415	407
CM with feedback	445	639	641	586	611

Table 5: Execution Time (ms) For Data Collected From Figaro sensors

	Classification features				
	Steady states	4 PCAs	5 PCAs	3 LDAs	4LDAs
BDT	298	381	379	309	304
KNN	325	404	412	337	320
ENN	235	288	412	337	320
CM without feedback	350	464	442	415	407
CM with feedback	445	639	641	586	611

Fig. 11 presents the results displayed at the GUI when the data are selected from the second data set collected using the 4×4 sensor, 80% of the data for training whereas the 20 % remaining for testing (5-fold cross validation). The identification is performed after using PCA with 5 PCs and adopting ENN as a classification approach. The data distribution is displayed in terms of PC-1, PC-2 and PC-4. The classification accuracy achieved is 93.28% and the computation time required is 259.02 ms for 5-fold cross validation.

Figure 11: Illustrative Example of Data Identification using ENN and PCA

Fig. 12 presents the results displayed at the GUI when the data are selected from the second data set collected from the Figaro sensors, 75 % of the data were used for training (4-fold cross validation). LDA is performed with 3 discriminant functions and BDT classifier was adopted. The 3-D data distribution is displayed in terms of DF-1, DF-2 and DF-3. The classification accuracy achieved is 95.31% and the computation time is increased to 1091.41 ms.

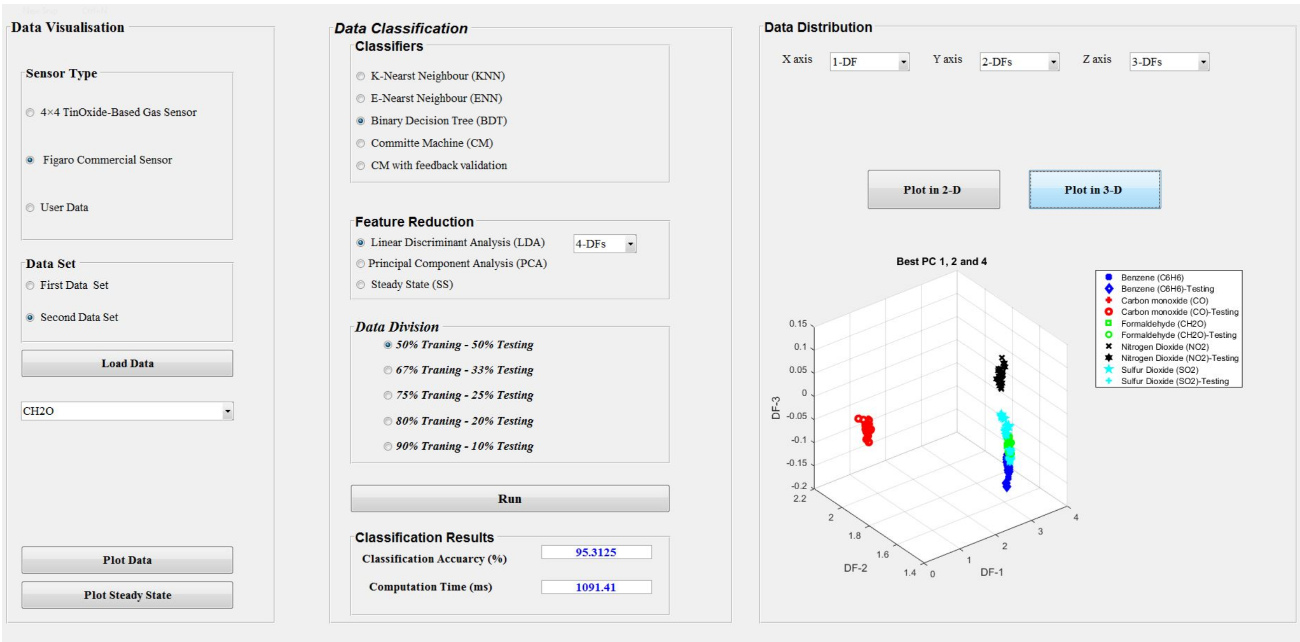


Figure 12: Illustrative Example of Data Identification Using BDT and LDA

6. Conclusion

This paper presents a software design for an interactive tool dedicated to a developed EN system for gas identification. The main objective of the GUI is to provide a simple approach to evaluate the performance of the EN platform. The data used in the EN system were collected from two different gas array sensors, in-house fabricated 4×4 sensor array and seven Figaro sensors. In addition, the various dimensionality reduction techniques and classification approaches algorithms have been used in order to evaluate several scenarios of the proposed EN system. The obtained results reveals that exploring CM approach will improve the classification accuracy up to 100 %. Moreover, applying dimensionality reduction techniques improves the classification accuracy compared with using the steady states values directly. Nevertheless, this improvement by incorporating CM with dimensionality reduction techniques come with cost of additional computation time. Thus, a trade-off between classification accuracy and computational time has to be made in order to determine the best approach for gas identification.

The GUI can be used to run several tests on the EN system in order to determine the techniques that render the best performance in terms of data classification and computation time. Furthermore, the design of the GUI provides the user with the opportunity of using another type of data in order to evaluate various applications based on pattern recognition algorithms.

Moreover, the GUI can be used to emulate the sensors behavior to connect directly or through a wireless communication channel with a Zynq SoC Platform.

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Highlights

- Introduce electronic nose (EN) system for gas monitoring and identification using different pattern recognition techniques.
- Develop an interactive user-friendly GUI for electronic nose used for gas monitoring and identification.
- GUI can be used as concept demonstrator to summarize all the functionalities of the EN system.
- A freely distributed stand-alone application to quantify different pattern recognition algorithms.